Interval and p-Box Techniques for Model Validation: on the Example of the Thermal Challenge Problem

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Realistic Measurement Situations

- \bullet Often, the measurement result z depends:
 - not only on the measured value x, but also
 - on the parameters s of the experiment's setting
 - and on the values of some auxiliary quantities y.
- The dependence z = f(x, s, y) is usually known.
- *Ideal case:* we know y, so we find x.
- $Real\ case$: we know y with some uncertainty.
- Usually: uncertainty in y leads to extra measurement error in x.
- Good news: often, we can combine multiple measurement results and decrease influence of y's uncertainty.
- We get sub-noise measurement accuracy: better than the accuracy with which we know y.

Example: Multi-Spectral Imaging

- We measure $\widetilde{I}(f, \vec{p}) = I(f, \vec{p}) + D(f, \vec{p})$, where:
 - $I(f, \vec{p}) = C(f) \cdot I(\vec{p})$ is the intensity of the source on frequency f at point p;
 - $D(f, \vec{p})$ is the intensity of dust radiation.
- ullet Often, $D\gg I$, so we cannot determine the object's structure.
- We know how D depends on f: $D(f, \vec{p}) = D(\vec{p}) \cdot f^{\alpha}$.
- ullet Here, $x=I,\, s=f,\, y=D,$ and $z=f(x,s,y)=C(s)\cdot x+y\cdot s^{\alpha}.$
- Based on two observations $z_i = C(s_i) \cdot x + y \cdot s_i^{\alpha}$, we can apply linear algebra ideas to eliminate y:

$$z_1 \cdot s_2^{\alpha} - z_2 \cdot s_1^{\alpha} = x \cdot (C(s_1) \cdot s_2^{\alpha} - C(s_2) \cdot s_1^{\alpha}).$$

• Result: we uncover previously unseen spiral and ringlike structures in distant galaxies.

VLBI Astrometry

- Very Large Baseline Interferometry (VLBI): we simultaneously observe a distant radiosource by two (or more) radioantennas i, j.
- *Ideal case:* time delay between the two antennas

$$\tau_{i,j,k} = \frac{1}{c} \cdot \vec{b}_{i,j} \cdot \vec{s}_k.$$

• Synchronization is not perfect $(\Delta t_i \neq 0)$, hence

$$\tau_{i,j,k} = \frac{1}{c} \cdot \vec{b}_{i,j} \cdot \vec{s}_k + \Delta t_i - \Delta t_j.$$

- Here, $z = \tau$, $x = \vec{s}_k$, $y = (\vec{b}_{i,j}, \Delta t_i)$.
- Measurement error in τ corresponds to accuracy $\approx 0.001''$, but inaccuracy in Δt_i is much worse.
- Differential astrometry:

$$\Delta \tau_{i,j,k,l} = \frac{1}{c} \cdot \vec{b}_{i,j} \cdot \Delta \vec{s}_{k,l},$$

where $\Delta \tau_{i,j,k,l} \stackrel{\text{def}}{=} \tau_{i,j,k} - \tau_{i,j,l}$, drastically improves the accuracy.

VLBI Astrometry: Arc Method

• To get rid of baseline vectors, we need 4 antennas:

$$\Delta \tau_{1,2,k,l} = \frac{1}{c} \cdot \vec{b}_{1,2} \cdot \Delta \vec{s}_{k,l}; \quad \Delta \tau_{2,3,k,l} = \frac{1}{c} \cdot \vec{b}_{2,3} \cdot \Delta \vec{s}_{k,l},$$
$$\Delta \tau_{3,4,k,l} = \frac{1}{c} \cdot \vec{b}_{3,4} \cdot \Delta \vec{s}_{k,l}.$$

- For the dual basis $\vec{B}_{i,j} \cdot \frac{1}{c} \cdot \vec{b}_{i,j} = \delta_{(i,j),(i',kj')}$, we get $\vec{s}_{k,l} = \Delta \tau_{1,2,k,l} \cdot \vec{B}_{1,2} + \Delta \tau_{2,3,k,l} \cdot \vec{B}_{2,3} + \Delta \tau_{3,4,k,l} \cdot \vec{B}_{3,4}$.
- Express $\vec{B}_{i,j}$ as a linear combination of $\vec{s}_{1,2}$, $\vec{s}_{1,3}$, $\vec{s}_{1,4}$.
- For any other source k, we have a similar expression $\vec{s}_{k,1} = \vec{s}_k \vec{s}_1 = \Delta \tau_{1,2,k,1} \cdot \vec{B}_{1,2} + \Delta \tau_{2,3,k,1} \cdot \vec{B}_{2,3} + \Delta \tau_{3,4,k,1} \cdot \vec{B}_{3,4}$.
 - Hence, \vec{s}_k is a linear combinations of $\vec{s}_{1,2}$, $\vec{s}_{1,3}$, $\vec{s}_{1,4}$.
 - We have a linear transformation T between the actual and the observed values \vec{s}_k .
 - Since $\|\vec{s}_k\| = 1$, T is rotation.
 - So, we can determine positions modulo rotation.

VLBI Imaging

- Problem: find the image $I(\vec{p})$.
- Solution: find Fourier transform $F(\vec{b})$ of $I(\vec{p})$.
- Ideal case: the phase shift $\widetilde{\varphi}_{i,j}$ between the signals observed by antennas i and j is equal to the phase $\varphi_{i,j}$ of $F(\vec{b}_{ij})$.
- In reality: due to synchronization errors $\Delta \varphi_i$,

$$\widetilde{\varphi}_{i,j} = \varphi_{i,j} + \Delta \varphi_i - \Delta \varphi_j.$$

- Here, $z = \widetilde{\varphi}_{i,j}, x = \varphi_{i,j}, y = \Delta \varphi_i$.
- Closure phase method eliminates the effect of the auxiliary parameters by considering the "closure phase" $\widetilde{\varphi}_{ij} + \widetilde{\varphi}_{jk} + \widetilde{\varphi}_{ki}$ for which:

$$\widetilde{\varphi}_{ij} + \widetilde{\varphi}_{jk} + \widetilde{\varphi}_{ki} = \varphi_{ij} + \varphi_{jk} + \varphi_{ki}.$$

Image Georeferencing

- Problem: find the relative orientation of geospatial images $I_1(\vec{p})$ and $I_2(\vec{p})$.
- Problem reformulated: find shift, rotation angle, and scaling between the images.
- Difficulty: to find an angle with accuracy of 1°, we need 360 tests; we need 4 parameters, so we need $360^4 \approx 10^9$ tests practically impossible.
- *Idea:* separate the problem find rotation angle and scaling separately from finding the shift.
- Fact: in Fourier domain, when $I_2(\vec{p}) = I_1(\vec{p} + \vec{a})$, then $F_2(\vec{\omega}) = F_1(\vec{\omega}) \cdot \exp(i \cdot \vec{\omega} \cdot \vec{a})$.
- Here, $x = F(\vec{\omega}), y = \vec{a}$.
- Solution: the shift-independent combination is the absolute value $|F_i(\vec{\omega})|$.

Measuring Strong Electric Currents

- Problem: measuring the cable current I at an aluminum plant.
- Specifics: I is difficult to measure directly.
- Specifics: I is measured by its magnetic field E.
- Ideal case (single cable): E = I/r, where r is the distance between the sensor and the cable's axis.
- Real plants: there is often an auxiliary nearby cable.
- Here, z = E, x = I, s = sensor locations, y = location and current in the auxiliary cable.
- Difficulty: z = f(x, s, y) non-linearly depends on the (unknown) location of the auxiliary cable.
- Solution: combining the measurements from different sensors eliminates the influence of the auxiliary cable.

Ultrasonic Non-Destructive Testing (in brief)

- *Problem:* find the location and orientation of hidden faults in a plate.
- Related active measurements:
 - send ultrasonic Lamb waves to the plate;
 - measure the waves that propagated along the plate.
- Difficulty: the resulting signals depend both on the location and on the orientation of the fault.
- *Idea:* separate the effects of location and orientation.
- Solution: by appropriately combining sensor readings, we can minimize the effect of location.
- Thus, we can easily determine the fault's orientation.

Formulation of the General Problem

- General problem:
 - Objective: we are interested in n_x scalar parameters that form x.
 - Measurement situation: each n_z -component measurement result z depends not only on x, but also on n_y components of the auxiliary quantity(-ies) y: z = f(x, s, y).
 - Desirable objective: determine x without knowing y precisely.
- Two possible situations:
 - y is fixed (cannot be varied), but we can change s. Example: multi-spectral imaging.
 - We cannot change the settings s, but we can use different values of y. Example: VLBI astrometry.

Variable Settings: Analysis of the Problem

- Situation: after we performed the measurement in N_s different settings s_1, \ldots, s_{N_s} , we get N_s measurement results z_1, \ldots, z_{N_s} .
- Situation: we do not know y.
- Conclusion: select N_s so that we will be able to uniquely determine both x and y.
- After N_s measurements, we have N_s n_z -component equations $z_i = f(x, s_i, y)$ to determine n_x unknown components of x and n_y unknown components of y.
- Fact: # of equations must be \geq # of unknowns.
- We have $N_s \cdot n_z$ scalar equations for $n_x + n_y$ unknowns.
- Recommendation: perform the measurements in at least $N_s \geq (n_x + n_y)/n_z$ different settings.

Practical Question: How to Solve the System of Equations?

- Difficulty: in general, the dependence z = f(x, y) is non-linear.
- So, we have a system of non-linear equations.
- What helps: often, we know good approximations $x^{(0)}$ and $y^{(0)}$ to x and y.
- How it helps:
 - We only need to find $\Delta x \stackrel{\text{def}}{=} x x^{(0)}$ and $\Delta y \stackrel{\text{def}}{=} y y^{(0)}$.
 - Usually, Δx and Δy are small.
 - So, we can expand f(x,y) in Taylor series in Δx and Δy and ignore 2nd and higher order terms.
 - As a result, to find Δx and Δy , we get an easier-to-solve system of *linear* equations.

Variable Settings: Example

- Case study: multi-spectral astronomical imaging.
- Reminder: $\widetilde{I}(f, \vec{p}) = C(f) \cdot I(\vec{p}) + D(\vec{p}) \cdot f^{\alpha}$.
- Here, $z = \widetilde{I}$, x = I, s = f, y = D, and

$$z = f(x, s, y) = C(s) \cdot x + y \cdot s^{\alpha}.$$

- Specifics: $n_z = 1$, $n_x = 1$, and $n_y = 1$.
- General recommendation: we must have at least $(n_x + n_y)/n_z = (1+1)/1 = 2$ settings.
- Confirmation: we have shown that, based on measurements in two different settings

$$z_1 = C(s_1) \cdot x + y \cdot s_1^{\alpha}, \quad z_2 = C(s_2) \cdot x + y \cdot s_2^{\alpha},$$

we can uniquely determine the desired value x:

$$z_1 \cdot s_2^{\alpha} - z_2 \cdot s_1^{\alpha} = x \cdot (C(s_1) \cdot s_2^{\alpha} - C(s_2) \cdot s_1^{\alpha}).$$

Different Values of y: Analysis

- General idea: we measure several (N_x) objects x_i .
- General idea: we measure each object under several (N_y) circumstances $y_j, j = 1, \ldots, N_y$.
- Based on the results $z_{i,j} = f(x_i, y_j)$ of these measurements, we must be able to determine x_i and y_j .
- Example: in VLBI astrometry example, we observe several sources x_i by using several radiotelescopes y_i .
- After $N_x \cdot N_y$ measurements of z, we get $n_z \cdot N_x \cdot N_y$ scalar equations.
- We must find N_x vectors x_i with n_x components/x.
- We must find N_y vectors y_j with n_y components/y.
- Recommendation: select N_x and N_y so that:

$$n_z \cdot N_x \cdot N_y \ge N_x \cdot n_x + N_y \cdot n_y.$$

Different Values of y: Good News and Bad News

- Recommendation: $n_z \cdot N_x \cdot N_y \ge N_x \cdot n_x + N_y \cdot n_y$.
- Good news: this inequality is true when N_x and N_y are large enough.
- Good news: often, we know reasonably good approximations $x_i^{(0)}$ and $y_j^{(0)}$, so we can linearize.
- Bad news: sometimes, we cannot uniquely determine x_i and y_j even for large N_x and N_y .
- Example: in astrometry, we cannot uniquely determine directions to the sources $\vec{s_i}$.
- Reason: if we rotate all the directions \vec{s}_i and $\vec{b}_{i,j}$, we get the same time delays.
- What we can determine in this case: coordinates of the sources $\vec{s_i}$ modulo rotations.

How Can we Describe Such Non-General Situations? Enter Transformation Groups

• Problem:

- we measure all the objects x for all the values y,
- we cannot determine all the values x and y.

• Reformulation:

- even when we know all the values f(x, y),
- there exist values $T_x(x) \neq x$ and $T_y(y) \neq y$ for which the measurement results are exactly the same:

$$f(x,y) = f(T_x(x), T_y(y)).$$

- Such pairs of transformations form a group G.
- We can only find x modulo transformations $\in G$.
- Example: in astrometry, we have rotations group.

Thermal Challenge Problem: In Brief

- Objective: make sure that:
 - for a manufacturing-related distribution of thermal properties k and ρC_p (as given by samples),
 - for given time t, thickness L, and heat flux q,
 - the probability P that a temperature T exceeds a given threshold T_0 should be $\geq 1 p_0$ (=0.99).
- We know: an approximate model $T \approx f(k, \rho C_p, t, L, q)$.
- Complexity: it is difficult to measure T for high q.
- We have performed:
 - several experiments for smaller q, and
 - one extra (accreditation) experiment for a large q.
- Problem: use the known data to check whether

$$P \stackrel{\text{def}}{=} \operatorname{Prob}(T \le T_0) \ge 1 - p_0.$$

Thermal Challenge Problem

- How this problems fits into our general framework:
 - measured quantity z: temperature z = T;
 - known auxiliary quantity: time $s_1 = t$;
 - unknown auxiliary quantities: $y_1 = k$, $y_2 = \rho C_p$;
 - we know the \approx dependence $z_1 \approx f(s_1, y_1, y_2)$.
- Additional complexity: the model is only approximate:

$$\left|z^{(k)} - f(s_1^{(k)}, y_1^{(k)}, y_2^{(k)})\right| \le \varepsilon$$

for some (unknown) accuracy ε .

• Natural idea: once, for a sample, we know $z^{(k)} = T$ for different moments $t = s^{(k)}$, we find y_1 and y_2 for which $\varepsilon \to \min$, where:

$$|z^{(k)} - f(s_1^{(k)}, y_1, y_2)| \le \varepsilon.$$

How to Implement the Above Idea

- Linearizable case: we know approximate values $y_1^{(0)}$ and $y_2^{(0)}$ such that the differences $\Delta y_i \stackrel{\text{def}}{=} y_i y_i^{(0)}$ are small (hence quadratic terms can be ignored).
- Resulting solution: solve a linear programming problem

$$\varepsilon \to \min$$

under the conditions

$$-\varepsilon \leq z^{(k)} - f(s^{(k)}, y_1^{(0)}, y_2^{(0)}) - \frac{\partial f}{\partial y_1} \cdot \Delta y_1 - \frac{\partial f}{\partial y_2} \cdot \Delta y_2 \leq \varepsilon.$$

- General case—use Newton's approach:
 - we solve a linearized system, find Δy_i ; then
 - we take $y_i^{(0)} + \Delta y_i$ as a new initial approximation;
 - repeat until the process converges.

Solving the Thermal Challenge Problem: First Approximation

- Objective: check that for given s, y_1 , and y_2 , we have $z \le z_0$ with probability $\ge 1 p_0$ (=0.99).
- Preliminary analysis: for each object v, we use the records $T_v(t)$ to find $y_1 = k$, $y_2 = \rho C_p$, and ε_v .
- Gauging the model's accuracy: we take $\varepsilon \stackrel{\text{def}}{=} \max_{v} \varepsilon_{v}$ as the measure of the model's accuracy.
- Reformulating the objective: check that $P_0 \stackrel{\text{def}}{=} \operatorname{Prob}(f(s, y_1, y_2) \leq z_0 \varepsilon) \geq 1 p_0.$
- Assumption: y_1 , y_2 are independent normally distributed; we find means and st. dev. from given data.
- Resulting approach: for these normal distributions, we check whether $P_0 \ge 1 p_0$ by using linearization (when z is also normal) or Monte-Carlo simulations.

Towards More Accurate Description

- Fact:
 - for some values of the parameters s_i , measurements are easier;
 - for some, they are more difficult.
- Example: for the thermal challenge problem, this parameter is the thermal flow $s_2 = q$.
- Consequence: we have more data for easier-to-measure values.
- Consequence: the model is more accurate for easier-to-measure values of the parameters
- How to take this fact into account:
 - instead of a single measure ε of the model's accuracy ε ,
 - we explicitly consider the dependence $\varepsilon(s_2,\ldots)$.

Towards More Accurate Description: Specific Implementation

- Selecting a model for $\varepsilon(q)$: due to scale-invariance, we take $\varepsilon(q) = \varepsilon_0 \cdot q^{\alpha}$ for some ε_0 and α .
- Preliminary analysis: for each experimentally tested q, based on all samples with given q, we find

$$\varepsilon(q) = \max_{v:q(v)=q} \varepsilon(v).$$

- Estimating parameters of the $\varepsilon(q)$ model: we must find ε_0 and α for which $\varepsilon(q) \approx \varepsilon_0 \cdot q^{\alpha}$.
- Algorithm: we use the Least Squares method (LSM) to solve a system of linear equations

$$\ln(\varepsilon(q)) \approx \ln(\varepsilon_0) + \alpha \cdot \ln(q)$$

with unknowns $\ln(\varepsilon_0)$ and α .

• Final step: we use the accreditation experiment to improve the accuracy of the $\varepsilon(q)$ model.

Additional Idea:

How to Simplify Computations

• Fact: in the given formula

$$T(x,t) = T_i + \frac{q \cdot L}{k} \cdot \left[\frac{(k/\rho C_p) \cdot t}{L^2} + \frac{1}{3} - \frac{x}{L} + \frac{1}{2} \cdot \left(\frac{x}{L}\right)^2 - \frac{2}{\pi^2} \cdot \sum_{n=1}^{6} \frac{1}{n^2} \cdot e^{-n^2 \cdot \pi^2 \cdot \frac{(k/\rho C_p) \cdot t}{L^2}} \cdot \cos\left(n \cdot \pi \cdot \frac{x}{L}\right) \right]$$

$$\rho C_p \text{ always appears in a ratio } \frac{k/\rho C_p}{L^2}.$$

- Resulting idea:
 - instead of $y_1 = k$ and $y_2 = \rho C_p$, - we should use $y_1 = \frac{q \cdot L}{k}$ and $y_2 = \frac{k/\rho C_p}{L^2}$: $T(x,t) = T_i + y_1 \cdot \left[y_2 \cdot t + \frac{1}{3} - x_0 + \frac{1}{2} \cdot x_0^2 - \frac{2}{\pi^2} \cdot \sum_{n=1}^6 \frac{1}{n^2} \cdot e^{-n^2 \cdot \pi^2 \cdot y_2 \cdot t} \cdot \cos(n \cdot \pi \cdot x_0) \right],$ where $x_0 \stackrel{\text{def}}{=} \frac{x}{L}$.

From Validating a Model to Improving a Model

- Assumption: the formula assumes that $y_1 = k$ and $y_2 = \rho C_p$ are constants.
- Fact: the average value \bar{k} of $y_1 = k$ grows with temperature T:

T	20	250	500	750	1000
$ar{k}$	0.49	0.59	0.63	0.69	0.75

• Natural conclusion: y_1 is a function of T; example:

$$y_1 \approx a + b \cdot T$$
; LSM: $a \approx 0.63$, $b \approx \frac{0.06}{250}$.

- Resulting idea: plug in $y_1(T) = y_1(20) + b \cdot T$ into the original formula and hope for the better fit.
- Another idea: try to match the difference between z and $f(s, y_1, y_2)$ by an empirical model.
- Example: try a linear dependence for this difference.

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